An Asynchronous and Non-Invasive Brain-Actuated Wheelchair

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1 Introduction

The possibility to act upon the surrounding environment without using our human nervous system's efferent pathways enables a new interaction modality that can boost and speed up the human sensor-effector loop. In recent years, brain-computer interface (BCI) research is exploring many applications in different fields: communication, environmental control, robotics and mobility, and neuroprosthetics [1] [2] [3] [4] [5] [6] [7]. Our work in the MAIA project[1] is focused on developing asynchronous and non-invasive BCI to control robots and wheelchairs [7] [8]. It means that the users control such devices spontaneously and at their own paced, by learning to voluntary control specific electroencephalogram (EEG) features measured from the scalp. To this end, the users learn how to voluntary modulate different oscillatory rhythms by execution of different mental tasks (motor and cognitive). To facilitate this learning process, machine learning techniques are utilized, both to find those subject-specific EEG features that maximize the separability between the patterns generated by executing the mental tasks [9], and to train classifiers that minimize the classification error rates of these subject-specific patterns [7]. Finally, to assist the control task, different levels of intelligence are implemented in the device jointly with shared control techniques between the two interacting agents, the BCI system and the intelligent device [10] [11].

One of the main challenges of a non-invasive BCI based on spontaneous brain activity is the non-stationary nature of the EEG signals. Shenoy and co-workers [12] describe two sources of non-stationarity, namely differences

[1] *MAIA—Mental Augmentation through Determination of Intended Action*, http://www.maia-project.org

between samples extracted from calibration measurements (training data set) and samples extracted during the online operation of the BCI system (test data set), and changes in the user's brain processes during the online operation (e.g., due to fatigue, change of task involvement, etc). Such kind of phenomena have motivated that BCI research groups develop adaptive algorithms to deal with these shifts in the distributions of samples [12] [13] [14]. Unfortunately, current adaptive solutions have two main limitations. Firstly, they are based on supervised approaches requiring the correct output for every sample and so the user cannot operate the BCI autonomously. Secondly, adaptation in the wrong moment (e.g., moments when the user is not executing properly the mental tasks because fatigue, distraction, etc) will incorrectly change the feedback (the device's behavior) and will disrupt user's learning process. Given this scenario, two questions arise. Is it possible to find (rather) stable subject-specific EEG features? How shared control techniques can minimize the impact of EEG non-stationarity?

In this paper we describe the first asynchronous brain-actuated wheelchair that can be operated autonomously and report results obtained by two subjects while driving a simulated version of the wheelchair. Our EEG-based BCI exhibits two key components, namely the selection of stable user-specific EEG features that maximize the separability between the different mental tasks, and the implementation of a shared control system [10] [11] between the BCI and the intelligent simulated wheelchair.

The paper is structured as follows. Sect. 2 describes the complete system and the experimental setup. Sect. 3 reports the results focusing on the system robustness over time and context (physical environment). Finally, Sect. 4 gives some conclusions and discusses future work.

2 Experimental Setup

The system is integrated by two entities, the intelligent wheelchair and the BCI system. Environmental information from the wheelchair's sensors feeds a contextual filter that builds a probability distribution $P_{Env}(C)$ over the possible user's mental steering commands, $C = \{\textit{Left, Right, Forward}\}$. The BCI system estimates the probabilities $P_{EEG}(C)$ of the different mental commands from the EEG data. Both streams of information are combined to produce a filtered estimate of the user's intent $P(C) = P_{EEG}(C) \cdot P_{Env}(C)$. The shared control system also uses the environmental information from the wheelchair's sensors to map these high-level commands into appropriate motor commands, translational and rotational velocities, that steer the wheelchair towards the desired direction while avoiding obstacles. Fig. 1 depicts a schematic representation of the shared control architecture of the brain-actuated wheelchair. See [11] for a detailed description. The BCI has two components, namely a feature extractor and a Gaussian classifier. The former selects the most relevant features of the EEG signals based on canonical variates analysis (CVA)

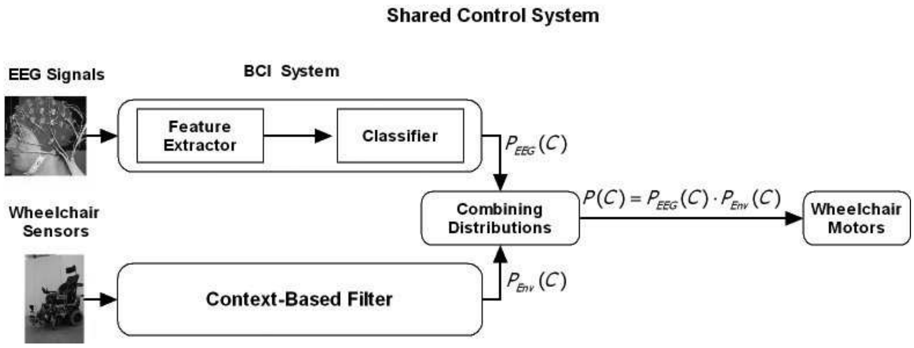

Fig. 1. Architecture of the brain-actuated wheelchair

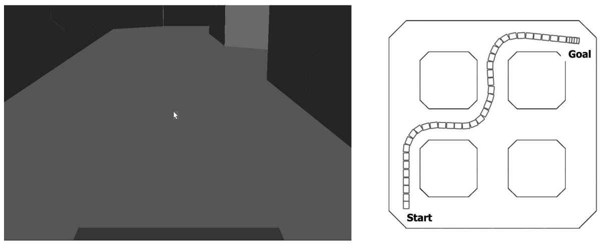

Fig. 2. *Left*: monitor display in a first person view from the Start. The white cursor at the center is the fixation point. The rectangle at the bottom is the simulated wheelchair. *Right*: top view of the simulated world and the pre-specified path.

[9]. Based on these features, the Gaussian classifier estimates the probability distributions of the three mental commands [7].

2.1 Task

The subjects were sitting in a chair looking at a fixation point placed at the center of a monitor. The monitor displayed a simulated wheelchair in a first person view placed in a simulated world. The subjects were asked to mentally drive the simulated wheelchair from a starting point to a goal following a pre-specified path by executing three different mental tasks (*left* hand imagination movement to turn *Left*, rest to go *Forward*, and words association to go *Right*). Fig. 2 depicts the monitor display and the pre-specified path. Every subject participated in 5 experimental sessions, each consisting of 10 trials. The time elapsed between two consecutive experimental sessions was variable: 1 day between sessions 1 and 2, 2 months between sessions 2 and 3, 1 hour between sessions 3 and 4, and finally 1 day between sessions 4 and 5.

2.2 EEG Data Acquisition and Preprocessing

Data were recorded from the 2 subjects with a portable Biosemi acquisition system using 64 channels sampled at 512Hz and high-pass filtered at 1Hz. Then, the signal was spatially filtered using a common average reference (CAR) before estimating the power spectral density (PSD) in the band 8-48 Hz with 2 Hz resolution over the last 1 second. The PSD was estimated every 62.5 ms (i.e., 16 times per second) using the Welch method with 5 overlapped (25%) Hanning windows of 500 ms. Thus, an EEG sample is a 1344-dimensional vector (64 channels times 21 frequency components).

2.3 Calibration Sessions and Feature Selection

To extract stable discriminant EEG features and build the classifier, both subjects participated in 20 calibration sessions recorded in the same day than the test driving session 1. The calibration sessions were recorded during the morning and the test driving session 1 during the afternoon. As in the driving sessions, the subjects were sitting in a chair looking at a fixation point placed at the center of a monitor. The display was also the same, the simulated wheelchair in a first person view (see Fig. 2 *Left*). The subjects were instructed to execute the three mental tasks (left hand imagination movement, rest, and words association) in a self-paced way. The mental task to be executed was selected by the operator in order to counterbalance the order, while the subjects decided when they started to execute the mental task. Each calibration session was integrated by 6 trials each, 2 trials of each class. The duration of each trial was 7 seconds but only the last 6 seconds were utilized in the analysis to avoid preparation periods. In these sessions the subjects did not receive any feedback, so the monitor display was static.

The data from the 20 calibration sessions were grouped in 4 blocks (B1, B2, B3 and B4) of 5 consecutive sessions. Taking into account the recordings timing, there were different configurations of training and testing sets (train-test): B1–B2, B1–B3, B1–B4, B2–B3, B2–B4, B3–B4, (B1+B2)–B3, (B1+B2+B3)–B4. Feature selection was done in a sequential way, where we first picked stable frequency components and then chose the best electrodes. To assess the stability of the frequency components we applied 21 canonical variates analysis (CVA), one per frequency component, on the training set of each configuration. For each canonical space we ranked the electrodes according to their contribution to (correlation with) this space [9]. Then, we built up to 24 linear discriminant classifiers, each using those electrodes that contributed more than $c\%$, with $c \in \{0.1, 0.2, ..., 0.9, 1.0, 2.0, ..., 15.0\}$. We used the stability of the classifier accuracy over the different configurations to select the frequency components. Afterwards, for each selected frequency, we took the configuration of electrodes (out of the 24 possible ones), that yielded the highest classification accuracy on the configuration (B1+B2+B3)–B4. Finally, we tested the different combinations of selected frequencies (with their associated electrodes) on the configuration (B1+B2+B3)–B4 and chose the best one. At the end of this sequential process the selected frequencies were 12 Hz for subject 1 and $\{10, 12, 14\}$ Hz for subject 2. We then built the statistical Gaussian classifier for each subject using their individual selected features from all the data of the calibration sessions.

2.4 Analysis

The system's robustness was assessed on three criteria, namely the percentage of goals reached, the BCI classification accuracy, and the shared control (the actual mental commands sent to the wheelchair after combining the probability distributions from the BCI and contextual filter) accuracy. The three criteria were analyzed over time (5 sessions) and context. For the contextual analysis, the path was split in 7 stretches. Thus, the system's performance was measured over the final goal (complete path) and subgoals (path stretches).

The analysis of the accuracies of the BCI and shared control has a main limitation since it requires to know the subject's intent. It is true, however, that in the experiments subjects had to inform the operator whenever they switched mental task so that the latter could label the data. Unfortunately, this approach is far from optimal. Indeed, providing this information interferes with, and so hampers, the driving task. As a consequence, the subject may deliver wrong or delayed mental commands leading to poor trajectories that the subject needs to correct by rapidly switching between mental commands—and the subject does not have time to inform the operator of all those switches and their exact timing. It follows that using the subject's stated intent for labelling data yields a pessimistic estimate of the accuracies of the BCI and the shared control. For this reason data was labelled in a different way. Each path stretch was labelled with the command that makes the wheelchair reach the next subgoal and, at the same time, we took into consideration the subject's stated intend. Only those samples where the subject's stated intent corresponds to the stretch label were utilized to compute the accuracies. Fig. 3 shows the 7 labelled stretches.

3 Results

This section is structured in two parts. The first part describes the system performance in terms of percentage of reached goals, average BCI classification accuracy and average shared control accuracy, over time and context. The second part describes the system performance on chosen single trials that show relevant emergent behaviors of the BCI system and the shared control system originated by their interaction in particular contexts.

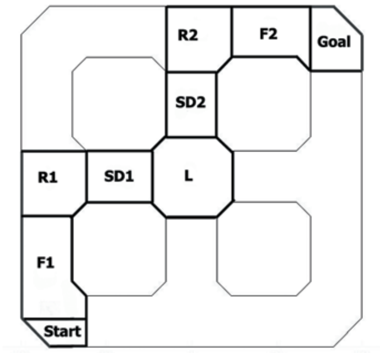

Fig. 3. Top view of the world and the path stretches. Stretches F1 and F2 were labelled as *Forward*, R1 and R2 labelled as *Right*, L labelled as *Left*, and SD1 and SD2 labelled as strategy dependent. The subjects can go through SD1 by means of two strategies, either executing *Forward* or executing *Right* followed by *Left*. Through SD2, subjects can execute either *Forward* or *Left* followed by *Right*

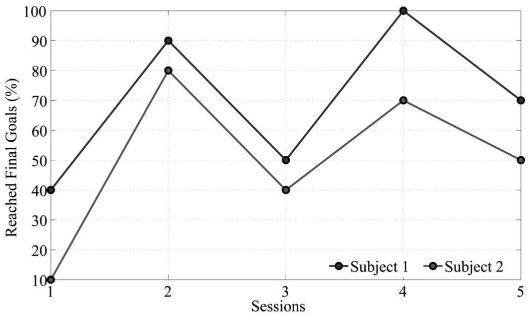

Fig. 4. Percentage of reached final goals over sessions. The time elapsed between sessions was: 1 day between sessions 1 and 2, 2 months between sessions 2 and 3, 1 hour between sessions 3 and 4, and 1 day between sessions 4 and 5

3.1 Global Performance

Fig. 4 depicts the percentage of final goals reached over the 5 sessions. Subject 1 reached more final goals in all the sessions. For both subjects, session 1 and session 3 are the sessions with less reached final goals (40% and 10% in session 1, 50% and 40% in session 3). Note that between session 2 and session 3 passed 2 months, so sessions 1 and 3 can be considered as sessions where the subjects learn (or re-learn, session 3) how to interact with the system and its dynamics. If these sessions were not considered, the average percentage of reached final goals are 86.7% and 66.7% for subjects 1 and 2, respectively. Regarding the maximum performances, subject 1 reached the final goal 100% of the trials in session 4, and subject 2 reached the final goal 80% of the trials in session 2.

Table 1. Percentage of local goals reached, average BCI classification accuracy and average shared control accuracy over the 7 path stretches

Subject	Criterion	Session	F1	R1	SD1	L	SD2	R2	F2
1	Local Goals Reached (%)	1	100	100	100	70	100	57	100
		2	100	100	100	90	100	100	100
		3	100	100	100	50	100	100	100
		4	100	100	100	100	100	100	100
		5	100	90	100	89	100	88	100
	BCI / Shared Control Accuracy (%)	1	18/45	73/62	20/40	62/50	18/33	53/47	23/67
		2	22/52	73/70	26/53	57/55	20/58	68/67	19/58
		3	34/62	70/59	22/46	42/37	15/78	69/63	29/85
		4	28/55	70/63	22/66	54/51	16/57	69/64	25/68
		5	33/62	56/51	29/62	53/52	29/63	56/47	30/75
2	Local Goals Reached (%)	1	100	10	100	100	100	100	100
		2	100	100	100	90	100	89	100
		3	100	100	100	40	100	100	100
		4	100	80	100	88	100	100	100
		5	100	100	100	50	100	100	100
	BCI / Shared Control Accuracy (%)	1	40/61	29/29	17/42	89/89	25/83	61/68	36/50
		2	33/41	71/68	40/62	57/59	26/48	66/65	35/61
		3	40/55	77/75	40/57	38/37	26/56	73/67	48/70
		4	38/46	62/63	46/62	49/53	38/48	77/77	35/61
		5	31/42	65/63	27/43	48/39	27/43	77/74	24/54

Table 1 displays the percentage of reached local goals, the average BCI classification accuracy and the shared control accuracy on each session over the 7 path stretches (local goals) for the two subjects. This table makes it clear the reasons why subjects couldn't reach the final goal—they failed sometimes to turn *Left* at the stretch L and/or to turn *Right* at the stretches R1 and R2. Interestingly, in these three stretches shared control performed generally worse than the BCI, what could indicate that subjects tried to deliver mental commands that the shared control system considers impossible to execute. On the contrary, shared control significantly improved the performance of BCI on the stretches F1, SD1, SD2 and F2, where the wheelchair was supposed to go straight. The average difference over these stretches is 35% for subject 1 (24% BCI vs. 59% shared control) and 21% for subject 2 (34% BCI vs. 55% shared control). These 'poor' accuracies of the BCI and shared control indicate that to drive the wheelchair straight subjects cannot simply deliver the mental command *Forward*, but needed to steer *Left* and *Right*. Furthermore, shared control helped to generate smoother trajectories.

Subject 1 failed to reach the final goal in session 1 because he couldn't turn *Left* in stretch L in 30% of the cases and, afterwards, he failed to turn

Right in 40% of the cases that he successfully arrived to stretch R2. In this session, subject 1 always performed correctly the optimal action for all other stretches he went through. As mentioned before, in these 'hard' stretches, L and R2, shared control degraded the BCI performance (50% vs. 62% in L and 47% vs. 53% in R2). Regarding session 3, subject 1 failed to reach the final goal because he couldn't turn *Left* in stretch L 50% of the cases. This was due to a low BCI accuracy (42%) and a lower shared control accuracy (37%). Finally, in sessions 2, 4 and 5 subject 1 reached the final goal 70% (or more) of the trials and each local goal over 88%.

Subject 2 failed to reach the final goal in session 1 because he couldn't turn *Right* in stretch R1 90% of the cases. This was due to a very low BCI and shared control accuracy (29%). In sessions 3 and 5, the poor final performance was due to failures in turning *Left* in stretch L—accuracies of 50% and 40%, respectively. As for subject 1, also in these two sessions shared control degraded the BCI performance although less severely (38% vs. 37% in session 3, 48% vs. 39% in session 5). Finally, in sessions 2 and 4 subject 2 reached the final goal 70% (or more) of the trials and each local goal over 80%.

3.2 System Performance in Single Trials

In this section we analyze the performance of the brain-actuated wheelchair in a few single trials to show emergent behaviors originated by the interaction of the BCI system and the shared control system in particular contexts. Experimental results show that subjects cannot execute a given mental task with the same level of proficiency all across the trajectories and over time. But, is this the only reason of the inter-trial differences in BCI classification accuracy for the same path stretch? We have observed that the interaction of the BCI system and the shared control system in a particular context plays also a significant role. We have already mentioned in the previous section that, for some stretches, shared control degraded the performance of the BCI, what could indicate that subjects tried to deliver mental commands that the shared control system considers impossible to execute. Here we take a closer look at this situation.

Table 2 shows the performance for subject 1 in session 4 for trails 2 and 8 in two stretches, R1 and R2, that requires the same command. In all cases subject 1 succeeded in making the wheelchair turn *Right*. However, the BCI and shared control performances were rather different. Thus, we can see that whenever the BCI accuracy is sufficiently high (92% in trial 2 stretch R1, 74% in trial 8 stretch R2) the shared control accuracy is much lower (67% and 53%, respectively). The opposite happens when the BCI accuracy is not that good (trial 2 stretch R2 and trial 8 stretch R1). The implication for the subjects is that they need to learn a model of the shared control system (and its interaction with the BCI) to develop successful driving strategies, otherwise their BCI proficiency cannot be fully exploited and, eventually, can hamper the behavior of the wheelchair. But for the subjects to learn that model they need to have a stable performance of the brain-actuated wheelchair. Table 2 shows that, in many cases, the shared control accuracy is rather stable independently of the performance of the BCI (see, in particular, trial 2).

Table 2. Inter-trial differences in performance: subject 1, session 4

Trial	Stretch	BCI Acc.	Shared control Acc.	Wheelchair Behavior
2	R1	92%	67%	*Right*
	R2	48%	68%	*Right*
8	R1	65%	76%	*Right*
	R2	74%	53%	*Right*

4 Conclusions and Future Directions

In this paper we have presented the first asynchronous and non-invasive EEG-based BCI prototype for brain-actuated wheelchair driving. The system can be autonomously operated by the user without the need for adaptive algorithms externally tuned by a human operator to minimize the impact of EEG non-stationarities. Our brain-actuated wheelchair has two key components. First, the selection of stable user-specific EEG features that maximize the separability between the patterns generated by executing different mental tasks. Second, the inclusion of a shared control system between the BCI system and the intelligent simulated wheelchair. The reported experiments with two subjects have shown that both were able to reach 90% (subject 1) and 80% (subject 2) of the goals one day after the calibration of the BCI system, and 100% (subject 1) and 70% (subject 2) two months later. It is worth noting that both subjects reached less goals in the first session, one hour after the calibration of the BCI system, and in the third, first session after two months of the calibration of the BCI system, sessions where the subjects learn or re-learn how to interact with the system and its dynamics.

In agreement with the results obtained in [11], the analysis over different path stretches has shown that the shared control system boosts the BCI performance when it is low, while it may even degrade it when the BCI performance is higher because the user driving strategy it is not compatible with the context-based filter. As a consequence, the subject has to learn when these situations occur in order to develop successful driving strategies compatible with rules of the shared control system. On the other hand, a low BCI accuracy does *not* necessarily imply that the BCI is not working correctly. This accuracy is *estimated* according to the user's stated intent and/or the optimal command for each stretch, while for a proper control of the wheelchair subjects need to make steering corrections and so switch rapidly between mental commands. For this reason we believe that the assessment of an intelligent brain-actuated device cannot simply be based on the BCI performance.

Finally, the negative effect that a fixed shared control system may have in the BCI performance illustrates the need for further research in adaptive schemes where the level of assistance provided by the shared control system is flexible and compensates the mental capabilities of the subject: it will help significantly when the subject's performance (BCI accuracy) is low whereas it will decrease its role when the BCI accuracy is very high.

Acknowledgments

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